The Grammar of Transformers: A Systematic Review of Interpretability Research on Syntactic Knowledge in Language Models

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Abstract

We present a systematic review of 337 articles evaluating the syntactic abilities of Transformer-based language models (TLMs), reporting on over 3,000 datapoints spanning a wide range of syntactic phenomena, languages, models, and methods. We take the data to collectively show that TLMs encode a non-trivial amount of syntactic knowledge. Behavioral evidence shows strong performance on formal syntactic phenomena, but weaker and more variable performance on phenomena at the syntax-semantics interface. Performance is also consistently lower for languages with less digital support. Probing and mechanistic studies further support the presence of syntactic knowledge in TLMs. Yet, because most work remains observational and current approaches are methodologically heterogeneous, insight into the detailed computational mechanisms underlying syntactic processing remains limited. At the same time, the literature remains heavily concentrated on English and BERT-like models. We discuss the implications of our results and provide recommendations for future research.

1 Introduction

It has been observed at least since Gulordava et al. (2018) that language models (LMs), though trained simply on a token prediction task, seem to acquire a non-trivial amount of syntactic knowledge. In recent years, a growing body of research has focused on understanding what precisely is learned and how it is used at processing time (e.g., Rogers et al., 2020; Lasri et al., 2022a; Brinkmann et al., 2025). However, even if some trends have emerged, there is yet no general picture about syntactic knowledge in LMs. We therefore think that it is a good moment to stop and appraise the extant literature. In this article, we do precisely that, through a **systematic review** (Page et al., 2021), a type of review that (to our knowledge) is not commonly used in computational linguistics (CL) and NLP. Systematic reviews differ from common narrative reviews in that they include transparent search, selection, and annotation criteria, and they provide quantitative evidence for the identified patterns. We focus on Transformer-based language models (TLMs) because they are the dominant model as of 2026.

The specific goals for this review are twofold: (i) mapping the landscape of research on syntactic knowledge in TLMs (what has been done and how; what remains to be done), and (ii) summarizing what is currently known about syntactic knowledge in TLMs.

Our work builds on six previous reviews with overlapping content: Limisiewicz and Mareček (2020), Linzen and Baroni (2021), Kulmizev and Nivre (2022), Chang and Bergen (2023), Millière (2024), and López-Otal et al. (2025). These reviews found that modern LMs acquire rich syntactic representations early during pretraining (Chang and Bergen, 2023), localize much of this information in their middle layers, and encode at least some syntactic relations via specialized attention heads and groups of neurons (López-Otal et al., 2025). The reviews also point out limitations of TLMs, including reliance on surface-level heuristics, lexical sensitivity, and challenges with rare constructions and subtle distinctions (Kulmizev and Nivre, 2022; Linzen and Baroni, 2021). While valuable, these prior reviews are largely narrative and interpretive. In contrast, we provide a quantitative and systematic synthesis of the literature with the aim of offering a transparent mapping between the available evidence and the conclusions, an approach that is increasingly necessary given the scale and methodological heterogeneity of the knowledge accumulated in recent years.

Our review covers 337 articles and 3,074 individual datapoints across different languages, syn-

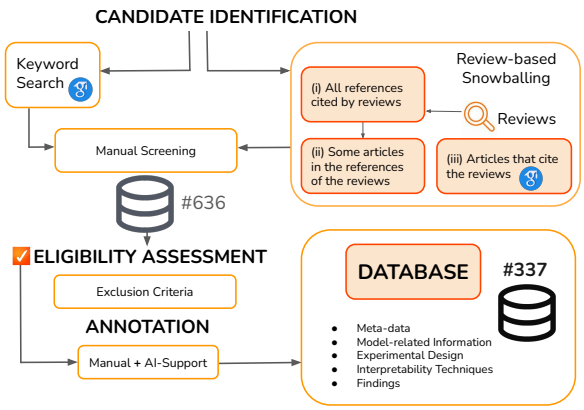

Figure 1: Flowchart summarizing database creation.

tactic phenomena, methods and datasets. We also contribute to the community an annotated database of the reviewed studies, to be made publicly available alongside the analysis code upon acceptance.

2 Method

Fig. 1 summarizes the process we followed to create the database, comprising paper candidate identification, eligibility assessment, and annotation. We did data collection in summer 2025, with a cut-off date for inclusion of July 31, 2025. Importantly, the database is designed to remain open to future extensions, with a form[1] allowing researchers to contribute and add new papers.

Paper candidate identification. In the initial identification stage, we prioritized recall, deferring concerns about precision to the subsequent stage. Article relevance was primarily assessed via its title (in case of doubt, we reviewed the abstract, and, if necessary, the full text). To identify candidates, we followed a two-pronged strategy: A *keyword search* in Google Scholar, using keywords that combined "syntactic structure/knowledge" and "LLMs/LMs/transformer", and a *snowballing strategy* using the six aforementioned reviews on the topic to identify relevant references. In the latter, we screened (i) all the references cited by the reviews,[2] resulting in 263 articles, (ii) some of the articles that were cited in these 263 articles, and (iii) most of the articles that cite the reviews themselves, identified via Google Scholar.[3] This yielded 636 articles.

Eligibility assessment. This stage shifted attention to precision. We excluded: 1) Studies focusing on non-transformer architectures (e.g., RNNs, LSTMs) or on encoder–decoder architectures, particularly those designed for machine translation, so as to keep articles within the scope of our research question. 2) Studies that, while analysing TLMs, do not empirically assess syntactic knowledge. 3) Publications without a clear empirical component, such as position papers or surveys (the previous reviews were not included in the analysis due to the absence of an empirical component). 4) Publications that were neither peer-reviewed journal articles, conference papers, nor archived preprints. This implies excluding blog posts and MA or PhD theses, since they often report on findings that are also published in peer-reviewed venues. The remaining 337 articles (cited in App. A, Table 1) were further annotated and analysed .[4]

Annotation. We defined 33 annotation variables, organized into five categories, to systematically capture the aspects of the selected works that would enable quantitative analyses and cross-study comparisons. An overview is provided below, with a detailed description in App. B.

The *meta-data* category includes publication details and information on how articles entered or exited the review process (source of each article and, if applicable, the grounds for exclusion). *Model-related* information specifies the model name(s), type(s), fine-tuning status, and language coverage. *Experimental design* codes the syntactic phenomena investigated, languages tested, and experimental materials employed. To establish the syntactic categories, we applied a bottom-up approach, starting from the terms used in the studies themselves and grouping them under broader labels recognizable to both the linguistics and NLP communities. The resulting 11 labels are shown in Fig. 2 (right) and described in detail in App. B. *Interpretability techniques* include the specific method, as named in the original paper, and a general category (behavioral, mechanistic, or probing, along the lines of Millière, 2024, see next section for more information). Further, we annotated various dimensions for probing and mech-

[1] Link after acceptance.

[2] Except for López-Otal et al. (2025), who provided a dedicated section of syntax-related studies in TLMs, and where we only considered the studies listed in that section.

[3] If a review had more than 100 citations, we reviewed the top 30-40% (sorted by relevance as determined by Google Scholar), otherwise all citations were checked.

[4] Excluded articles and exclusion reasons were retained for transparency and future studies beyond the scope of this review.

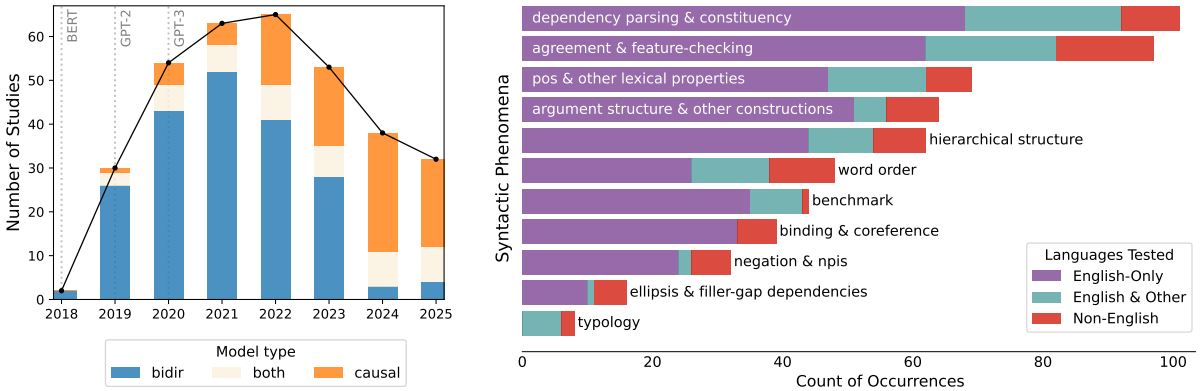

Figure 2: **Left:** Number of studies published each year; debut of influential models. **Right:** Counts of syntactic phenomena by evaluated language (only English tested, English and other languages, and non-English).

anistic studies, covering methodological aspects, causal nature, locality and strength of evidence of syntactic awareness. The *findings* category summarizes, in prose, the main insights regarding syntactic competence and processing as well as any model comparisons.

We produced annotations manually for 28 of the 33 categories; for the remaining 5 (model type, syntactic phenomena, experimental materials, method name, and main syntactic findings) we used a semi-auomated AI-assisted workflow to extract some information from the papers; final labels were determined manually. The AI workflow was successfully validated against a manual gold standard (further details are provided in App. C).

3 A Quantitative Overview of the Field

Fig. 2 (left), which shows the distribution of papers by year, indicates that interest in the topic of our review quickly took off after the appearance of BERT (Devlin et al., 2019), peaking in 2022 and decreasing afterwards (though note that the 2025 data only covers up to July, so the final count will likely exceed that of 2024). As expected, initially most work focused on bidirectional TLMs, but in later years, causal models have dominated. Also note that most studies focus on one model type (either bidirectional, 59%, or causal, 28%), with very few comparing the two (13%).

Beyond the information shown in Fig. 2 (left), we found that studies predominantly evaluate monolingual models (66%, the vast majority English), rather than multilingual (20%) or both kinds (14%). Also, consistent with previous observations (Waldis et al., 2024; López-Otal et al., 2025), most of the results in our database concern a single model: BERT, with 30% of the results. BERT plus variants account for 58% of the datapoints, and the four overall most studied models for 62%. The over-focus on BERT is likely due to BERT's early availability, strong baseline performance, and suitability for a wide range of research questions. As the field matures, research is increasingly moving toward a broader and more principled selection of architectures.

Linguistic phenomena & language diversity. Fig. 2 (right) shows that the distribution of syntactic phenomena is severely imbalanced: Most research has been conducted on formal syntax (c.f. *dependency parsing and constituency*, *agreement and feature-checking*, *POS and other lexical properties*—with most studies in this category focusing on POS—, *hierarchical structure*, and *word order*). These are phenomena that are relatively easy to get at with current NLP tools, especially for English. Instead, phenomena at the syntax-semantics interface have received much less attention (cf. *binding and coreference*, *negation and NPIs*, *ellipsis and filler–gap dependencies*); and only a handful of studies concern typological aspects. Somewhat surprisingly, only 42 studies used benchmarks, 29 of which used BLiMP (Warstadt et al., 2020a).[5] Fig. 2 (right) also showcases the overwhelming dominance of English (in purple), which we already noted regarding the models (here, the data shows the languages *tested* in the articles, not the languages covered by the model).

Methods. Recall from above that we follow Millière (2024)'s classification of interpretabil-

[5]The others were the CoLA task from GLUE (Wang et al., 2018, 11 uses), SyntaxGym (Gauthier et al., 2020, 3 uses), Holmes and HANS (McCoy et al., 2019; Waldis et al., 2024, 1 use each).

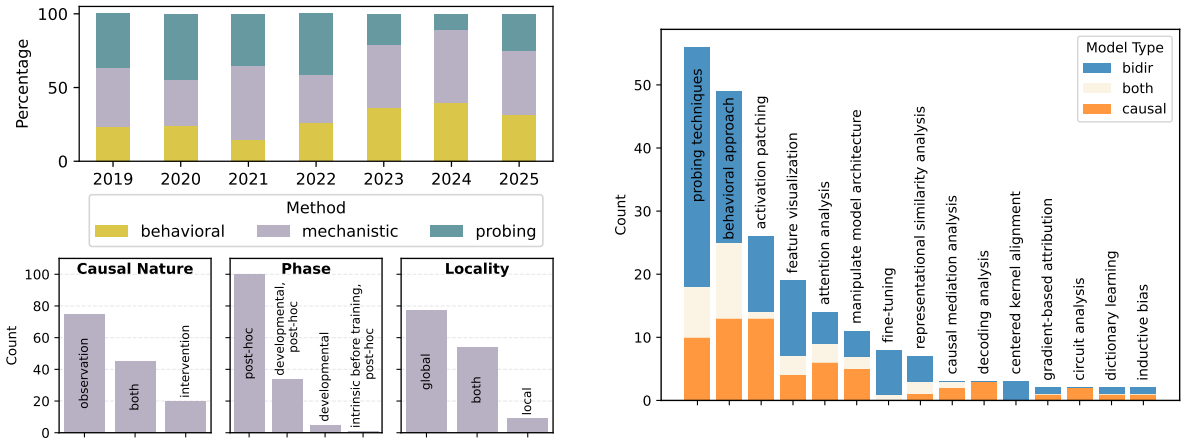

Figure 3: **Left:** Top: Percentage of methods over years. Bottom: mechanistic interpretability methods broken down by causal nature, training phase, and locality. **Right**: Most frequent interpretability techniques used in mechanistic papers; methods may be combined.

ity methods into behavioral, probing, and mechanistic, as it provides a useful framework for organizing the literature. Fig. 3 (left-top) shows a relatively balanced distribution of these methods over the years. Behavioral methods assess models based on their output behavior at the final layer. They include analysis of generated outputs and comparisons of model probabilities in controlled settings (e.g., minimal pairs, Linzen et al., 2016; Lau et al., 2017). The latter paradigm, highly influenced by the psycholinguistic tradition, treats the higher probability of a correct form compared to an incorrect alternative as evidence that the TLM has mastered a given syntactic construct. Probing is a specific interpretability method that became very popular after Hewitt and Manning (2019) introduced it, which is why it is in a category on its own. It aims at detecting specific types of linguistic information in the models' internal representations, most often by training auxiliary classifiers on activations from specific layers (Waldis et al., 2024). The argument goes that if, for instance, a classifier trained to recover the POS of input words from a given hidden layer is successful, then that layer encodes POS information. Finally, mechanistic approaches actually cover a wide array of specific methods, see Fig. 3 (left-top) for the most common ones. These methods may (and often do) incorporate behavioral or probing elements. In our database, we categorized studies investigating internal dynamics, even if including behavioral or probing tests as well, as mechanistic. Overall, mechanistic approaches aim at getting at internal mechanisms by inspecting model components (e.g., layers, neurons, circuits, or training dynamics) and, where possible, intervening on them to causally link representations to behavior (Wiegreffe and Saphra, 2024). For instance, these methods may modify the activations of components identified as syntactically crucial and test the effects of these interventions on model behavior.

All methods have their pros and cons. For instance, probing offers scalability and clear feature detection but, on its own, lacks causal insight: decoding linguistic features is not equivalent to showing that the identified representations are actually used in predictions (besides other issues, see Belinkov, 2022; Wiegreffe and Saphra, 2024; Agarwal et al., 2025). Therefore, it is reassuring that the field has been using a healthy variety of methods throughout (Fig. 3, left-top). The only significant temporal trend is that probing methods have diminished substantially in recent years, possibly due to the growing awareness of their limitations.However, there is one aspect that we believe should improve: There are still too few studies that can get at causal mechanisms (only 19% use interventional methods, see App. D, Fig. 13).

We next delve a bit more into mechanistic studies, largely following the taxonomy from Bereska and Gavves (2024). We annotated the 140 mechanistic papers in our database by considering (i) the causal nature of the specific method (observational, interventional, or both; Fig. 3, left-bottom, *Causal Nature*); (ii) which stage of the TLM lifecycle is investigated, intrinsic (before training), developmental (during training), or post-hoc (after training; *Phase* in Fig. 3); (iii) which part or scale of the model the analysis targets, ranging from global representations (e.g., the residual stream)

to local units (e.g., individual neurons; *Locality*); and (iv) the specific methods used, as described by the authors (with some generalization; the most frequent are shown in Fig. 3, right). We find over 80 specific methods in mechanistic studies, which we take to be a positive development since interpretability is still young field.[6] Post-hoc analysis of fully trained models at a global level clearly dominates. However, there is a healthy amount of papers that track development, and many also check both global and local trends. Additional results for this section can be found in App. D.

4 Syntactic Knowledge in TLMs

We report on behavioral evidence derived from papers that measure model accuracy, before turning to results from probing and mechanistic approaches. We provide additional results for this section, including complete statistical model specification, in App. E.

4.1 Behavioral Evaluation

In the following, we report on benchmark results for English (as this is a controlled setup where results are comparable) and on results from non-benchmark studies for 113 languages (offering a broader but more heterogeneous view).

BLiMP. The BLiMP benchmark (Warstadt et al., 2020a) is designed for behavioral evaluation of models through minimal pair comparison. Our analysis includes English BLiMP scores from 25 papers: 11 that report by-category results and 14 that report average BLiMP scores. Fig. 4 (left) shows accuracies by phenomenon (an average of 31 datapoints per category, as most articles analyze multiple models; note that we include only results from fully trained models). The most salient feature of these results is how well the models perform on this benchmark. Notably, the best TLM is at or above human performance for 7 out of the 11 categories, and all but 8 out of the 368 results are above the baseline. Another salient feature is the large within-phenomenon variance across TLMs. We find that this variance is mostly driven by how good each model is at syntax generally, as measured by its overall BLiMP score: Model rankings across phenomena are highly consistent. This is illustrated in Fig. 4 (left) by highlighting the best (purple star) and worst (yellow dot) TLMs, and Fig. 16 in App. E.1 provides quantitative support. In this respect, additional analyses of average BLiMP scores confirm the expected scaling trend: larger TLMs and TLMs trained on more data generally achieve higher performance (see App. E.1).

Despite the large variance, the results also clearly suggests that TLMs perform better on formal syntactic relations (e.g. all agreement categories have medians over 85%) than on phenomena at the syntax-semantics interface (binding, argument structure, NPI licensing, control/raising, quantifiers and island effects all have medians below 75%). One exception is ellipsis: despite its reliance on interactions between syntax and semantics, several TLMs match or outperform humans on this category. However, BLiMP evaluates only specific cases of noun phrase ellipsis, whose violations may be comparatively easy to detect (Warstadt et al., 2020a), suggesting this result may reflect dataset characteristics rather than ellipsis as a phenomenon being easy for models.

More generally, despite its value for enabling cross-model comparisons across phenomena, BLiMP still provides limited coverage of syntax, even for English. It focuses on cases that can be readily expressed as minimal pairs and aggregates heterogeneous cases into composite scores with equal weighting, potentially obscuring important differences in difficulty and relevance (Kulmizev and Nivre, 2022). As a result, model performance should be interpreted with the characteristics and limitations of the benchmark in mind.

Beyond benchmarks and English. We next aggregate all the non-benchmark accuracy scores from the database, yielding 1,557 datapoints from 76 studies spanning 113 languages. Fig. 4 (right) presents results for our annotated categories of linguistic phenomena. The variance this time is even greater than in the BLiMP case, which is not surprising given that different studies use different materials and test different languages. However, since this makes for an unclear picture at a descriptive level, we turn to statistical modeling to investigate the factors influencing accuracy. In particular, we use as predictors syntactic phenomena, model type (causal / bidirectional), and language support to see how syntactic knowledge

[6] Recall that mechanistic papers often include also probing and behavioral methods, and indeed they show in the figure as the two most frequent approaches even within mechanistic papers.

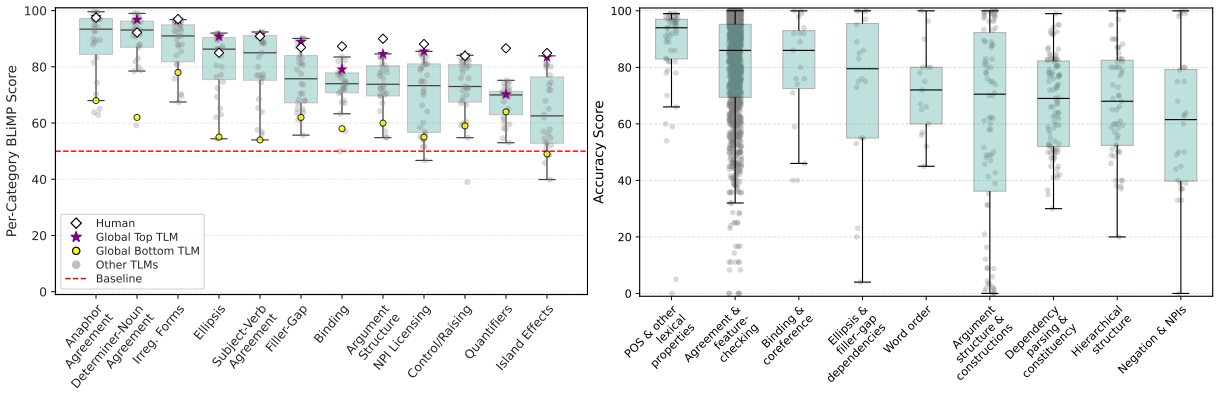

Figure 4: **Left**: **BLiMP (English-Only)** scores by category. Human performance ◇ from Warstadt et al. (2020a). Top ⋆ (Roberta large) and bottom ● (Minibert) TLM among those with complete per-category results. **Right**: **Accuracy scores (113 languages)** by linguistic phenomena, covering more than 1,500 data points from 76 studies. Note that 77% of the datapoints for Agreement & feature-checking originate from one study (Jumelet et al., 2025).

varies across languages. Language support gets at the availability of NLP resources and datasets for a given language. We take the support data from Joshi et al. (2020), who define a 5-level classification ranging from low- to high-support. We fit a regression model and find that both model type and language support are significant predictors of accuracy scores: causal models outperform bidirectional models by 10% points ($\beta = 0.1$, $p < 0.001$). In addition, as could be expected, performance increases with language support, with each higher support category associated with a gain of 5% points ($\beta = 0.05$, $p < 0.001$). The estimated intercepts for the linguistic phenomena categories (App. E.2, Fig. 18) confirm that *POS and other lexical properties* and *agreement and feature-checking* have generally higher accuracies than average, while *hierarchical structure*, *negation & NPIs* and *argument structure & constructions* have lower accuracies. For the other phenomena, there is no evidence either way. Thus, this analysis largely confirms that formal syntactic phenomena are easier for TLMs than phenomena at the syntax-semantics interface.

4.2 From Behavior to Internal Mechanisms

Probing. Probing has been used to localize layers where syntactic information is most readily available. We code the the 56 probing-based studies that include this information (including mechanistic papers that also use probing) for the model locations at which studies report the strongest probing performance. Fig. 5 (left) shows that the middle layers are most commonly identified, corroborating previous observations (López-Otal et al., 2025).[7] This aligns with a view of TLM representations as distributed across layers, motivating analyses of how information accumulates and transforms throughout the network. In this vein, some mechanistic studies examine progressive knowledge encoding (e.g., He et al., 2025b), consistent with staged interpretations of decoder-only models that reflect a transition from surface-level cues to deeper syntactic and hierarchical processing (Lad et al., 2024).[8]

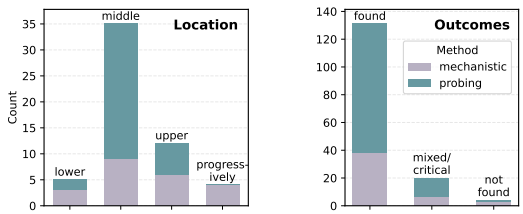

Figure 5: Probing-based studies. **Left:** location in TLMs where probing performance/syntactic knowledge is strongest. **Right:** author-reported evidence for syntactic representations in TLMs. Note that some mechanistic papers include probing methods; these are included.

Furthermore, we check 147 probing-based studies for their outcomes: Each study was coded according to whether probing recovered syntactic information from TLM representations, yielded mixed results, or failed to recover such infor-

[7] Despite the prominence of middle layers, studies typically describe them as showing stronger, rather than exclusive, encoding of syntactic information. We also observed that the distinction between "middle" and "upper" layers is somewhat subjective and varies across studies.

[8] Unlike a strict pipeline interpretation (e.g., Jawahar et al., 2019), this staged view does not assume discrete functional modules, but rather a gradual and overlapping transformation of representations across depth (e.g., Niu et al., 2022b).

mation. Fig. 5 (right) shows the results. 85% of studies report successful recovery of syntactic information from model representations. Although this high success rate may partly reflect publication bias toward positive results, this again points to substantial syntactic knowledge in TLMs. Additional analyses do not reveal substantial differences across syntactic phenomena in whether studies successfully recover syntactic information from model representations (App. E.3, Fig. 20). This contrasts with behavioral results, which do show clear differences in how easily models handle different syntactic phenomena. The mismatch provides further support to the idea that successful probing is not, by itself, a reliable measure of the quality or functional use of syntactic representations in TLMs (Agarwal et al., 2025).

Mechanistic interpretability. We tried to systematize the mechanistic studies to obtain more insights into the syntactic mechanisms in TLMs, but we faced a major challenge: once studies are broken down by method and phenomenon to enable meaningful comparisons, the resulting groups become too sparse and heterogeneous for a straightforward synthesis. We therefore decided to instead focus on author-reported strength of evidence for the presence of syntactic knowledge, similarly to what we did for probing studies. The results, shown in Fig. 6, are positive: 79% of the 140 mechanistic papers in our database find clear supporting evidence. At the same time, Fig. 6 again underscores that the vast majority of this evidence comes from studies focusing exclusively on English. Again, we fail to observe salient differences across phenomena, but all the syntax-semantics-interface phenomena have low coverage in the mechanistic literature, so this is still an open point (see App. E.4, Fig. 21).

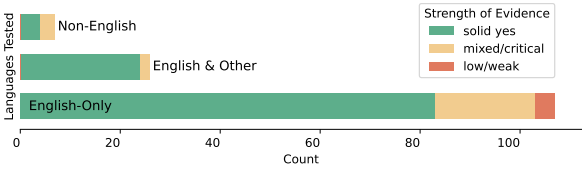

Figure 6: Evaluation of syntactic awareness in mechanistic interpretability studies by language tested.

5 Discussion & Conclusion

Conducting systematic reviews in CL/NLP. To our knowledge, this is among the first systematic reviews in CL and NLP. As the field of AI continues to grow at breakneck speed, systematic reviews and meta-reviews will become ever more important, as in other large fields like Medicine. However, conducting such reviews is challenging, and we have found some current practices in the community that make it even more challenging. We propose two main recommendations moving forward. First, studies should report complete data, to allow for meaningful comparison of results. Many papers included only partial data on models and methods, despite the fact that results crucially depend on factors like architecture, size, tokenization, and training data. Benchmark reporting is also often partial (e.g., only 11/25 papers include BLiMP per-category results). Additionally, documenting task framing and prompting is crucial, as these can also significantly impact outcomes (e.g., zero-shot vs. few-shot). Second, we should collectively standardize investigations to a greater extent. Differences in how syntactic phenomena are defined fragment results and limit comparability, as even the notion of "syntactic knowledge" varies across studies.[9] We offer a typology of syntactic phenomena that has been built in a bottom-up fashion from the current literature, and which could be refined and expanded upon as the field grows.

Standardization is particularly important for cross-linguistic research. We have shown a huge variance in cross-linguistic performance, only partially accounted for factors like the digital support of a language or the type of linguistic phenomenon. One of the main drivers, presumably, are the characteristics of the specific data the models are being tested on, but those can vary; compare for instance determiner-noun number agreement (easy) versus long-distance subject-object agreement (hard). Therefore, a standardization effort needs to be made in creating multilingual benchmarks, beyond direct translations or adaptations of English datasets (e.g., as in Baucells et al., 2025; Jumelet et al., 2025), as we otherwise risk overlooking language-specific phenomena. As an example of a "best of both worlds" approach that both standardizes and allows for variation, the Spanish variant of SyntaxGym (Pérez-Mayos et al., 2021) incorporates language-specific

[9] For instance, Waldis et al. (2024) place several of the phenomena we have considered here outside of syntax (e.g. negation in reasoning, and negative polarity item licensing in semantics).

features like subjunctive mood and flexible word order besides English-compatible phenomena.

The state of the field. Our review reveals a vibrant area of research, with plenty of studies and a healthy variety of methods (337 papers and more than 3,000 individual results are included in our database). The literature also shows substantial transfer of theoretical and methodological insights from psycholinguistics to model interpretability, enabling more principled comparisons between human and model behavior and strengthening links to linguistic theory.

However, on the negative side, we find an overstudy of a single language (69% of the articles are on English only, and 91% include English) and a few models (30% of the results concern BERT; including BERT and its variants raises the total to 58%), which severely limits the robustness and generality of the conclusions. In addition, while formal syntactic phenomena such as agreement, syntactic structure, word order, and morphosyntactic properties such as part of speech have been well studied, the syntax–semantics interface remains comparatively underexplored: phenomena such as binding, coreference, negation, ellipsis, or filler-gap dependencies have received very little attention. Expanding research to cover the syntax-semantics interface is particularly necessary given that we have found that in general models perform worse at it than at more formal aspects of syntax.

At a methodological level, at this stage of the research, some methods are established (behavioral, probing) and others are still emerging (under the broad umbrella "mechanistic"). Overall, however, we find an overuse of purely observational methods (81%), at the expense of causal approaches that can link model behavior to internal mechanisms. While we encourage the use of interventional methods, we emphasize that no single method is sufficient in isolation, and that the strongest evidence ultimately comes from combining observational and interventional paradigms (e.g., Simon et al., 2024; Agarwal et al., 2025; Acevedo et al., 2026). Also, the field has mostly focused on analyzing trained models at a global level; it should pay more attention to the emergence of syntactic knowledge during training and to the connections between local and global representations and mechanisms.

Syntactic knowledge in TLMs As for what TLMs learn about syntax through the language modeling task, the evidence suggests: a whole lot. For instance, TLMs perform quite well on the English BLiMP benchmark (average score of 72%, against a 50% random baseline), and between 79 and 85% of the analyzed studies identify syntactic knowledge in TLMs. Even accounting for the effect of publication bias (only positive results tend to be submitted), we take the literature to show that TLMs do encode a non-trivial amount of syntactic knowledge.

As for factors influencing performance, as mentioned above, we find that models perform better at formal syntactic phenomena than phenomena close to the syntax–semantics interface. As could be expected, larger models and models trained with more data tend to perform better; and performance degrades for lesser-resourced languages. Importantly, we also find that models that perform well on some syntactic phenomena tend to perform well across others, suggesting a general syntactic ability rather than phenomenon-specific strengths. As for internal mechanisms, probing data supports the view that much of syntactic processing occurs in the middle layers (López-Otal et al., 2025). However, there is still limited mechanistic understanding of why such representations emerge or how they support downstream computation. Given the current heterogeneity of the field, and that mechanistic methodologies and reporting practices are still evolving, we leave a broader synthesis of mechanistic insights to future work.

To sum up, the current literature supports the view *that* TLMs possess remarkable syntactic capabilities. However, understanding *how* this knowledge is acquired and used, as well as how it relates to universality and variation in language, will require more work in both the analysis of existing literature and new studies. We encourage greater methodological harmonization, more explicit theoretical commitments, and a broader empirical landscape. Some open topics are whether TLMs implement near-symbolic mechanisms, as hypothesized Boleda (2025); when and how TLMs fall back on superficial statistical patterns (e.g. performance on agreement, binding, or scope often degrades for rare or nonce lexical items, Lasri et al., 2022a); whether improvements with model scale reflect genuine generalization or massive memorization of specific instances (Lake and Baroni, 2018). We hope that our review, database, and annotation standard contributes to moving the field forward.

Limitations

For feasibility, this study focuses on Transformer-based language models and textual input, thus our findings may not fully generalize to recurrent or other neural architectures. Also, we conducted the keyword search in English, which likely led to under-retrieval of publications written in languages other than English. Note, however, that this was only one of the 3 strategies we used to identify relevant literature. Finally, our database is necessarily incomplete and evolving; the resource is intended to remain interactive and expandable as the field progresses. We see this work as a foundation that invites continued contributions and updates from the research community.

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A References

Table 1 lists the studies included and analyzed in our database. The entries are organized first by publication year and then sorted alphabetically by the authors' names.

Table 1: The 337 studies included in the database, sorted by year and alphabetically.

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Table 1: The 337 studies included in the database, sorted by year and alphabetically. (Continued)

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B Annotation dimensions

This section gives more details on the annotation dimensions used in the database and lists the specific COLUMN NAME. Additional information on variable levels and coding schemes will be made publicly available in the repository's README.

B.1 Meta-Data

We publish the main information about the study (ID, SHORT_REF, URL, YEAR, TITLE, ABSTRACT), and information of its review process:

Source for the article: REVIEW, indicates where the article was sourced from with chronological line of adding papers. Tracks the order of inclusion from different sources.

Exclusion grounds: EXCLUSION_GROUNDS, indicates the reason for exclusion.

B.2 Model-related information

Model type: MODEL_TYPE, categorized as:

- **Bidirectional:** At least one bidirectional model is featured (e.g., BERT, LSTMs).
- **Causal:** At least one causal model is featured (e.g., GPT, LSTMs).
- **Both:** Both model types are featured (e.g., comparative experiments with BERT, GPT, and LSTM).
- **Other:** Cases with neither causal nor bidirectional models, either excluded or meeting special inclusion criteria, e.g., specific analysis of encoder component of a Transformer architecture.

Model name and post-processing: MODEL_NAME_COMMENT, for the comment string, as specific as possible it is stated in the paper. MODEL_NAME, we post-process this string into a list of dictionaries, regard the following example:

1. Name as reported in the paper, e.g., *bert_base_uncased*.
2. Name enriched with post processing script: e.g., *family* ="BERT" plus mention of size, BERT-base.
3. Final example: list({*string* ="bert_base_uncased", *family* ="BERT", *size* = base, *case* = uncased}).

Fine-tuned: FINE_TUNED, indicates whether fine-tuning was performed.

Language coverage: MODEL_LANGUAGE_COVERAGE

- **Monolingual:** One language from scratch or continually pretrained (e.g., GPT2, BERT, ruBERT).
- **Multilingual:** Trained on multiple languages simultaneously from scratch (e.g., mBERT, GPT3).
- **Both:** Studies comparing monolingual and multilingual models.

B.3 Experimental design

Syntactic phenomena:

- **General:** SYNTACTIC_PHENOMENA, bottom-up annotation, starting from general to more specific cases. See Table 2.
- **Specific:** SPECIFIC_PHENOMENA, as referred to by authors.

Languages tested and post-processing: LANGUAGES_TESTED_COMMENT, for the comment string, as specific as possible it is stated in the paper. LANGUAGES_TESTED, we post-process this string into a list of all languages used in the experiments. LANGUAGES_TESTED_ENG_INCLUDED, indicates whether English was tested. LANGUAGES_TESTED_MONOLINGUAL_ENG, indicates whether only English was tested. LANGUAGES_TESTED_LANG_COUNT, number of tested languages.

Fine-tuning materials: FINE_TUNING_MATERIALS, resources used for fine-tuning in the experiments.

Experimental materials: EXPERIMENTAL_MATERIALS_COMMENT, materials as referenced by authors and summarized through AI-based workflow. EXPERIMENTAL_MATERIALS, annotated in post-processing to indicate whether they are naturalistic language or controlled stimuli, both, or "unknown" (if under-specified/referring to other's paper dataset).

B.4 Interpretability techniques

General: INTERP_CATEGORY, categorized as:

- **Behavioral:** Methods based on last layer input–output behavior.

Phenomena	Description
Benchmarks	Aggregated evaluation suites combining multiple syntactic phenomena (e.g. BLiMP, CoLA, SyntaxGym), often reporting composite performance metrics rather than phenomenon-specific analyses.
Dependency parsing & constituency	Structural representations of sentence form, including dependency relations, constituency trees, and syntactic functions (e.g., subject vs. object), without targeting hierarchical depth or processing complexity.
Hierarchical structure	Properties of abstract hierarchical organization independent of specific formalisms, including tree depth, recursion, center embedding, attachment ambiguity, and structural complexity.
Word order	Constraints on the linear ordering of words and phrases, including canonical and non-canonical orders, scrambling, and variation in surface order.
Agreement & feature-checking	Morphosyntactic dependencies involving grammatical features such as number, gender, person, and tense, typically requiring local or semi-local syntactic constraints.
POS & other lexical properties	Lexical-level categories and features, such as part of speech, verbal subcategorization, or lexical aspect; excludes tasks like named entity recognition that are primarily semantic or discourse-driven.
Negation & NPIs	Licensing and interpretation of negation and negative polarity items, involving interactions between syntax, semantics, and scope.
Binding & coreference	Constraints on anaphora and antecedent resolution, including reflexives, pronouns, and coreference relations, typically requiring hierarchical and discourse-sensitive representations.
Ellipsis & filler–gap dependencies	Long-distance dependencies such as wh-movement, gap filling, and ellipsis resolution, requiring sensitivity to abstract structure beyond linear proximity.
Typology	Cross-linguistic variation in syntactic patterns and constraints, including agreement systems, and constructional differences across languages.
Argument structure & constructions	Systematic syntactic patterns linking form and meaning, including argument realization, alternations (e.g. active/passive, dative alternation), relative clauses, and other constructional schemas at the syntax–semantics interface.

Table 2: The 11 Linguistic phenomena of our survey with brief definitions, which we annotated and organized from general Benchmark, to those focusing on syntactic structure and surface-level form (blue-purple tones) to form-and-function-related categories.

- **Probing:** Methods training a classifier on top of a given TLM layer.
- **Mechanistic:** Methods investigating internal dynamics, may incorporate behavioral or probing elements.

Specific: INTERP_METHOD, specific techniques description, named as in the original paper.

Probing: PROBING, classification of results to claim evidence for syntactic representations in the TLM.

Location: PROBING_LOCATION, specific location article states where performance peaks within the model.

Mechanistic Interpretability: We use the taxonomy introduced by Bereska and Gavves (2024) to characterize key dimensions: We annotated each mechanistic paper, 140 in total, along these dimensions:

- **Method:** MECHANISTIC_METHOD, string as general as possible as it is stated in the paper.
- **Causal Nature:** MECHANISTIC_CAUSAL NATURE, ranges from purely observational to interventional approaches.
- **Phase:** MECHANISTIC_PHASE, the phase distinguishes post-hoc from intrinsic approaches applied during model development.
- **Locality:** MECHANISTIC_LOCALITY, describes the level of analysis, ranging from individual components (e.g., neurons, attention heads) to full model architectures (e.g., residual stream).

Syntactic Awareness: MECHANISTIC_SYNTACTIC EVIDENCE/ AWARENESS captures whether mechanistic interpretability studies claim evidence of syntactic awareness of TLMs.

B.5 Findings

Main findings on syntactic knowledge: MAIN_FINDINGS, summarizes the findings of studies on how TLMs handle syntax, and their syntactic knowledge.

C AI-Based Workflow for Information Extraction

During the review process, we developed a semi-automated strategy combining NotebookLM (Google Labs, 2023) and ChatGPT (OpenAI,

Category	Question
Model information	
- Model type	*Which model do they test and which languages, do they do finetuning?*
Experimental design	
- Syntactic phenomena	*What are the "Syntactic phenomena, the Specific: list set as referred to by authors"*
- Experimental materials	*What is the "Experimental materials: naturalistic language, controlled stimuli"*
Interpretability techniques	
- Method name	*What is the Specific method name as referred to by the authors?*
Findings	
- Main findings on syntactic knowledge	*What are the main findings, especially on syntactic knowledge in the LM?*

Table 3: Questions used for AI-based information extraction.

2025) for structured information extraction on 5 variables, model type, syntactic phenomena, experimental materials, method name, and main syntactic findings, listed in Table 3.

Each paper was first analysed using NotebookLM (Google Labs, 2023) by posing a series of targeted questions to extract relevant details for these categories. The responses generated by NotebookLM were then summarized into a coherent paragraph using ChatGPT (OpenAI, 2025),[10] which we subsequently reviewed and used to populate the database. We specifically chose to prompt for paragraph-style summaries to maintain compact, integrated information for the database, rather than fragmented notes.

See Fig. 22 for an example. The workflow was iteratively refined during the course of the review process until it stabilized; starting at paper ID 120, this approach was applied without further adaptation. Following the validation of our approach, as described in the next section, we decided to publish the "main_findings" column of the database exclusively with LLM-generated output.

C.1 Validation of the Approach

To assess the reliability of our semi-automated information extraction strategy, we compared the AI-assisted summaries against the first, manually collected information ("gold" set, $n = 91$). Our evaluation confirmed that the semi-automated workflow captured the exact key details as the manual article review consistently, while improving efficiency. See Fig. 23 for an example. The summaries were AI-rated by ChatGPT (OpenAI, 2025) on a scale from 0 (completely unrelated) to 5 (equivalent), with a median score of $\bar{x} = 4.1$. The AI-assisted summaries tend to be more detailed and insightful for keyword searches, providing richer context. By contrast, the manually collected information was generally shorter, more general, and abstract, often relying on direct quotations and omitting specific details such as model comparison, task descriptions, and numeric results.

C.2 Limitations of Workflow

Some linguistic phenomena referenced in articles pertained to related work rather than the studies' own experiments, which can introduce ambiguity in AI-assisted summaries. During the manual annotation of the general syntactic phenomena, we identified and corrected a few such cases, but minor residual errors may remain.

C.3 Illustrative Figures

We provide screenshots from the workflow and interactions with the models in Fig. 22 and Fig. 23.

D Additional Results to Section 3

D.1 Additional Results to the Overview

We plot the coverage of model type and TLMs language coverage in Fig. 8. Most work focuses on a single model paradigm, primarily bidirectional models (59%) or causal models (28%), with only a small fraction directly comparing both (13%); similarly, evaluations largely target monolingual

[10] August 2025 release, incorporating GPT-4 and GPT-5 models

Phenomenon	N	Acceptable Example	Unacceptable Example
ANAPHOR AGR.	2	*Many girls insulted themselves.*	*Many girls insulted herself.*
ARG. STRUCTURE	9	*Rose wasn't disturbing Mark.*	*Rose wasn't boasting Mark.*
BINDING	7	*Carlos said that Lori helped him.*	*Carlos said that Lori helped himself.*
CONTROL/RAISING	5	*There was bound to be a fish escaping.*	*There was unable to be a fish escaping.*
DET.-NOUN AGR.	8	*Rachelle had bought that chair.*	*Rachelle had bought that chairs.*
ELLIPSIS	2	*Anne's doctor cleans one important book and Stacey cleans a few.*	*Anne's doctor cleans one book and Stacey cleans a few important.*
FILLER-GAP	7	*Brett knew what many waiters find.*	*Brett knew that many waiters find.*
IRREGULAR FORMS	2	*Aaron broke the unicycle.*	*Aaron broken the unicycle.*
ISLAND EFFECTS	8	*Whose hat should Tonya wear?*	*Whose should Tonya wear hat?*
NPI LICENSING	7	*The truck has clearly tipped over.*	*The truck has ever tipped over.*
QUANTIFIERS	4	*No boy knew fewer than six guys.*	*No boy knew at most six guys.*
SUBJECT-VERB AGR.	6	*These casseroles disgust Kayla.*	*These casseroles disgusts Kayla.*

Figure 7: Table from Warstadt et al. (2020a); minimal pairs from each of the 12 linguistic phenomenon categories covered by BLiMP. Column *N* records the number of different subphenomena exemplifying the relevant general phenomenon, 67 in total.

TLMs (66%), while multilingual (20%) and both monolingual–multilingual settings (14%) remain underexplored.

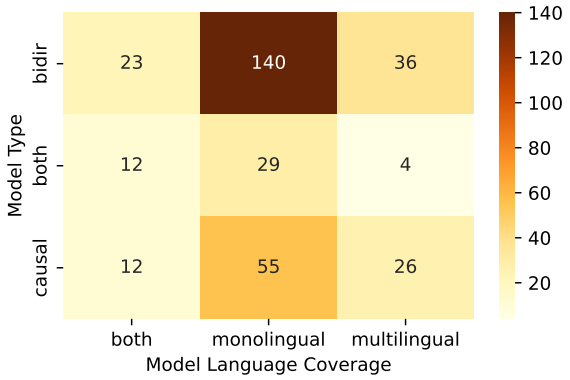


Figure 8: Count distribution by model type and language coverage.

We identified 54 unique TLMs and 609 non-duplicate model instances in the database; models were counted once per study and grouped by family or model name when appropriate (e.g., studies comparing BERT-base, BERT-large, or cased/uncased variants contributed a single BERT count). Fig. 9 shows that most of the results in our database focus on a single model, BERT, which accounts for 30% of all TLMS results. BERT and its variants together represent 58% of the datapoints, while the four most extensively studied models account for 62% overall.

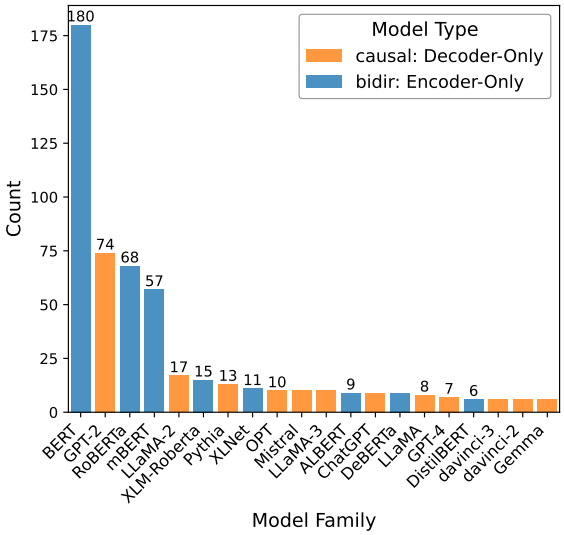


Figure 9: The 20 most frequently used TLMs. TLMs are counted once per study and grouped by family or model name when available (e.g., one BERT count for studies comparing BERT-base/large/(un)cased). Overall, the database includes 54 unique TLMs and 609 non-duplicate instances across studies, as illustrated above.

D.2 Additional Results to Linguistic Phenomena

Model type & language. Regarding coverage across TLMs, the distribution varies notably across syntactic phenomena, with the bidirectional TLMs dominating most phenomena (ranging from ∼60% to 73%) evaluation, while causal and both model types were more often tested on phenomena like *POS and other lexical properties* and *dependency parsing and constituency* (<20%). Regard

Fig. 19 for a distribution of studies across syntactic phenomena, model type, and interpretability method. When looking at the composition of phenomena within each model type, Fig. 10, *agreement and feature-checking* and *dependency parsing and constituency* constitutes the majority across all TLM tasks. Phenomena such as *argument structure and other constructions* is more prominent in causal TLMs.

Moreover, 62% of the articles focus on only one syntactic category, with 24% testing two, Fig. 11. This reflects a common emphasis on individual syntactic phenomena, which should not be interpreted as a limitation in itself. Rather, progress in the field benefits from combining fine-grained, phenomenon-specific analyses with more holistic approaches, as there is no single or definitive test for syntactic competence.

Across syntactic phenomena, monolingual TLMs dominate coverage in most categories (typically around ∼50–65%), while studies testing both and multilingual TLMs tend to contribute moderately (usually 15–30%) depending on the phenomenon, see Fig. 12.

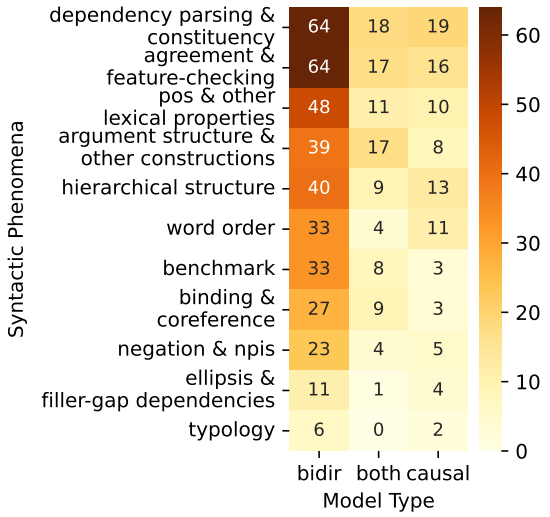


Figure 10: Heatmap of counts illustrating model type and syntactic phenomena.

D.3 Additional Results to Methods

Fig. 13 shows the counts of methods over the years, categorized according to whether they are observational or interventional. Notably, a significant temporal trend is that probing methods have diminished substantially in recent years, possibly due to the growing awareness of their limitations. For instance, following the publication of the influential criticism in Belinkov (2022), the number of probing studies with bidirectional TLMs in our database declined sharply, from 27 studies in 2022 to just 11 in 2023.

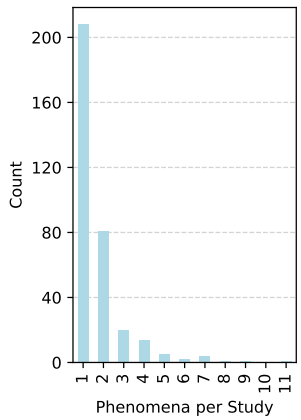


Figure 11: Counts of syntactic phenomena investigated per study.

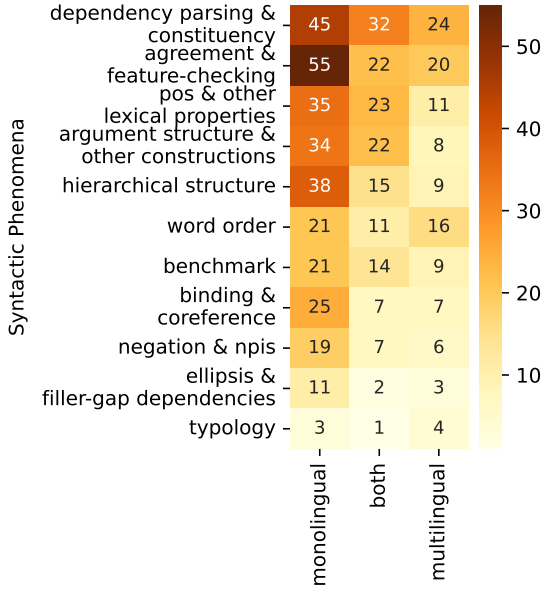


Figure 12: Counts heatmap of model language coverage and syntactic phenomena.

Linguistic phenomena. Fig. 14 shows a largely balanced distribution of methods across syntactic phenomena, with three notable exceptions. First, behavioral methods dominate for the phenomena that are most clearly at the syntax-semantics interface: *negation & NPIs* and *binding and coreference*. Second, mechanistic methods dominate in *benchmark*-based evaluations. Third, probing methods dominate in *dependency parsing & constituency* and *POS & other lexical properties*; for the latter, again we suspect this is an artifact of time, since these were among the first phenomena

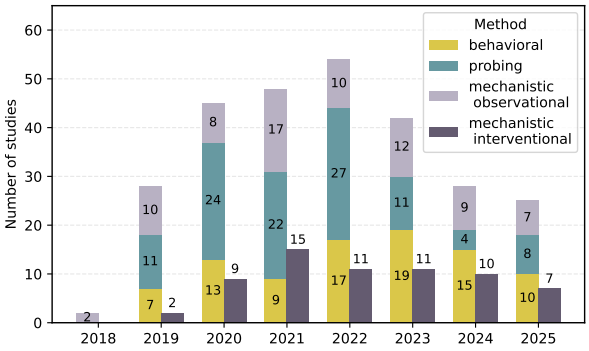


Figure 13: Counts of methods over years, grouped by observational and interventional approaches.

to be checked frequently with probing methods in earlier years. Moreover, tasks related to POS tagging and lexical properties are generally easier to formulate as classification problems than phenomena such as binding or argument structures, which may also contribute to this pattern.

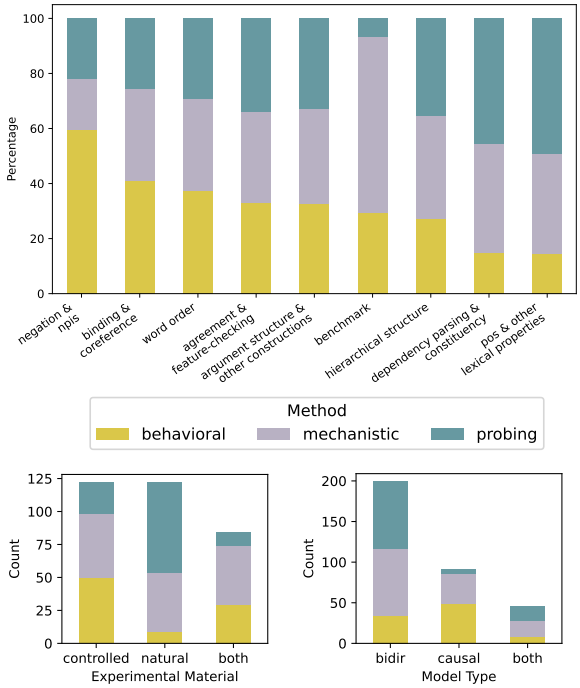


Figure 14: **Top:** Percentages of methods across syntactic phenomena; only phenomena with more than 20 instances are included. Linguistic phenomena are sorted by percentage of behavioral method. **Bottom:** Counts of experimental materials and model types by method (*unknown* experimental material with fewer than 10 counts excluded).

Experimental material. With respect to experimental materials, instead, clear differences emerge (Fig. 14, bottom left). Probing approaches (dark green) occur more frequently with naturalistic than with controlled data, particularly when targeting lexical or morphosyntactic properties such as POS (see Fig. 14, top); however, this pairing reflects an empirical co-occurrence rather than a methodological dependency, as the easy availability of e.g. POS annotations makes naturalistic data a convenient, but not necessary, choice for probing. Probing methods are instead almost absent in studies with causal TLMs (Fig. 14, bottom-right); we suspect that this is a historical accident, as most studies of causal TLMs have been carried out in 2024-25, when probing methods have become less common (note, however, that as mentioned above many mechanistic methods include some probing component).

Behavioral methods (lime yellow) pattern most frequently with controlled data, which makes sense given that many existing psycholinguistic datasets can be adapted to test TLMs, as behavioral methods need carefully designed data to test for a given property. Thus, the frequent pairing of behavioral methods with controlled data reflects the adaptation of psycholinguistic paradigms to test models, satisfying the need for carefully designed data to test specific properties.

E Additional Results to Section 4

E.1 Additional Results to BLiMP

Fig. 15 (top) shows the average BLiMP scores as a function of training data size, color-coded by model type. The first thing to note is how good models are according to this benchmark: the overall BLiMP score is 72% (random baseline: 50%). We also observe the well-known scaling pattern in deep learning: TLMs trained on larger amounts of data tend to perform better (linearly in log scale), as do larger TLMs (see also Fig. 15, bottom).

As for the difference between model types, note that, for a given size or amount of training data, bidirectional models tend to outperform causal models (as also observed in Waldis et al., 2024). Since BLiMP uses sentence-level comparisons, this cannot solely be due to the fact that bidirectional models, but not causal models, have access to the whole context of the stimulus when they process the critical fragment (e.g. *themselves/herself* in the first example in Fig. 7). We hypothesize instead that bidirectional models reach better sentence representations due to the bidirectional nature of the training task. However, for larger amounts of training data and model sizes

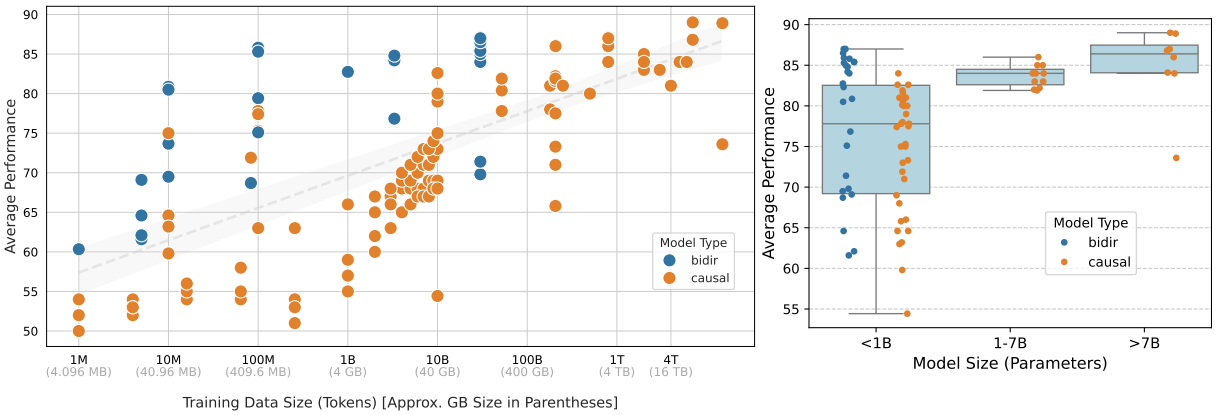


Figure 15: **Left:** BLiMP (Warstadt et al., 2020a) average scores plotted against the number of training tokens (log scale). **Right:** BLiMP average scores shown by model size and model type. If a paper reports scores for TLMs trained on varying sizes of training data, we include only the fully trained models in the boxplot.

	coeff.	SE
Intercept	77.57***	(1.85)
Model Type (causal)	-9.13***	(2.10)
Training Data Size (in billions)	0.0017***	(0.00)
Observations	134	
R^2	0.198	
Adj. R^2	0.186	
BIC	1003	
AIC	994	

Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 4: OLS regression predicting average BLiMP accuracy scores. Standard errors in parentheses.

(>30B training tokens and >1B parameters) only causal models have been examined in the literature we cover, such that we cannot know whether the trend continues at these scales.

Statistical modeling. We fit an OLS regression model predicting average BLiMP accuracy scores, 134 data points in total. Full model specifications and estimates are reported in Table 4. Although the explained variance is modest ($R^2 = 0.186$, $AIC = 994.3$, $BIC = 1003$), both model type and training data size were significant predictors: causal models performed worse ($\beta = -9.13$, $SE = 2.095$, $p < 0.001$), and training data size showed a small positive effect ($\beta = 0.0017$, $SE = 0.0$, $p < 0.001$). The intercept ($\beta = 77.57$, $SE = 1.848$, $p < 0.001$) represents the expected score for a bidir TLMs at zero training data (represented in billions of tokens).

Variance across phenomena. We ranked TLMs by performance within each linguistic phenomenon and added slight jitter to handle ties. Then, we computed Kendall's τ correlations between these rankings across linguistic phenomena categories to see how similarly models perform on different linguistic phenomena. Fig. 16 presents a heatmap with the correlation score between each phenomenon. Kendall's τ correlations show strong and consistent relationships across most linguistic phenomena, with an average correlation of about 0.58 (SD $\approx$ 0.14), indicating very strong agreement in TLM performance across tasks. Quantifiers are a clear outlier, exhibiting weak to moderate correlations with other categories. In contrast, several pairs show especially high alignment, notably Argument Structure and Control/Raising (τ = 0.82) and Filler-Gap and Island Effects (τ = 0.75).

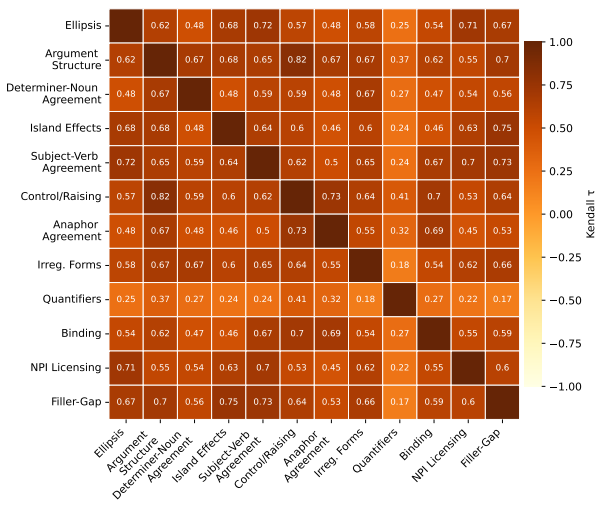


Figure 16: Computed model rankings per phenomenon, then Kendall's τ coefficient, visualized as a heatmap.

E.2 Additional Results to Beyond Benchmark and English

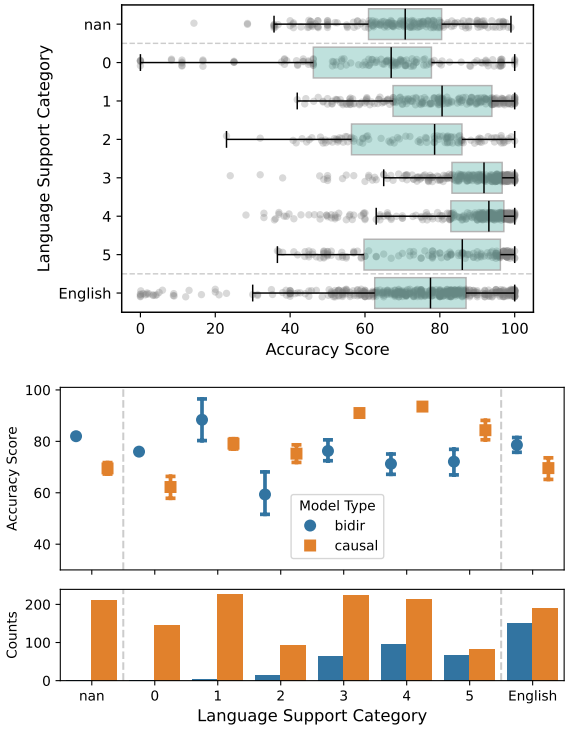


Figure 17: **Top:** Language support categories, categories taken from Joshi et al. (2020), with nan and English (category 5.) separately. **Bottom:** Mean accuracy scores by language group and model type.

Fig. 17 displays the distribution of TLM accuracy scores grouped by language support, based on the five categories reported by Joshi et al. (2020) and model type (bottom).

Statistical modeling. We estimate an OLS regression model predicting accuracy scores as a function of model type, linguistic phenomenon, and language support category. To ensure comparability across languages, we exclude instances with missing language support annotations (i.e., "nan" category in Fig. 17), as well as all scores annotated as *benchmark*. The resulting analysis is performed on 1,577 observations. Language support is treated as an ordered categorical variable (following Joshi et al. (2020)). Full model specifications and estimates are reported in Table 5, and a forest plot of the estimated coefficients is shown in Fig. 18.

E.3 Additional Results to Probing

We analyze 147 studies in total that employ probing methods, which includes all papers coded as probing, plus some coded as mechanistic when they also employed probing methods. Fig. 20 shows that probing-based studies successfully identify syntactic information at comparable rates across linguistic phenomena categories.

	coeff.	SE
Intercept	0.43***	(0.02)
Model Type (causal)	0.099***	(0.01)
Language support	0.05***	(0.003)
Agreement & feature-checking	0.17***	(0.01)
Argument structure	-0.17***	(0.02)
Binding & coreference	0.06	(0.04)
Dependency parsing	-0.003	(0.02)
Ellipsis & filler–gap depend.	-0.06	(0.04)
Hierarchical structure	-0.09***	(0.02)
Negation & NPIs	-0.11**	(0.03)
POS & other lexical properties	0.19***	(0.03)
Observations	1577	
R^2	0.23	
Adj. R^2	0.22	
BIC	-784.1	
AIC	-843.1	

Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 5: OLS regression predicting accuracy scores. Standard errors in parentheses.

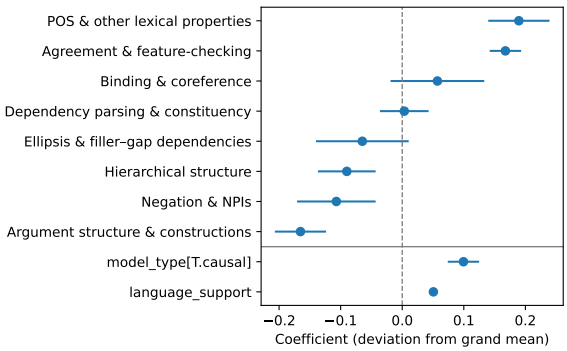


Figure 18: Forest plot of OLS regression coefficients predicting accuracy scores. The model includes model type, linguistic phenomenon (except *benchmark*), and language support category. Points represent coefficient estimates and horizontal lines indicate 95% confidence intervals.

E.4 Additional Results to Mechanistic Interpretability

We aim to characterize the mechanistic interpretability field by categorizing all 140 mechanistic papers by level of analysis and method. To abstract over this diverse set of approaches and assess what TLMs learn about syntax, we evaluate whether studies report evidence of syntactic knowledge or instead highlight its limitations.

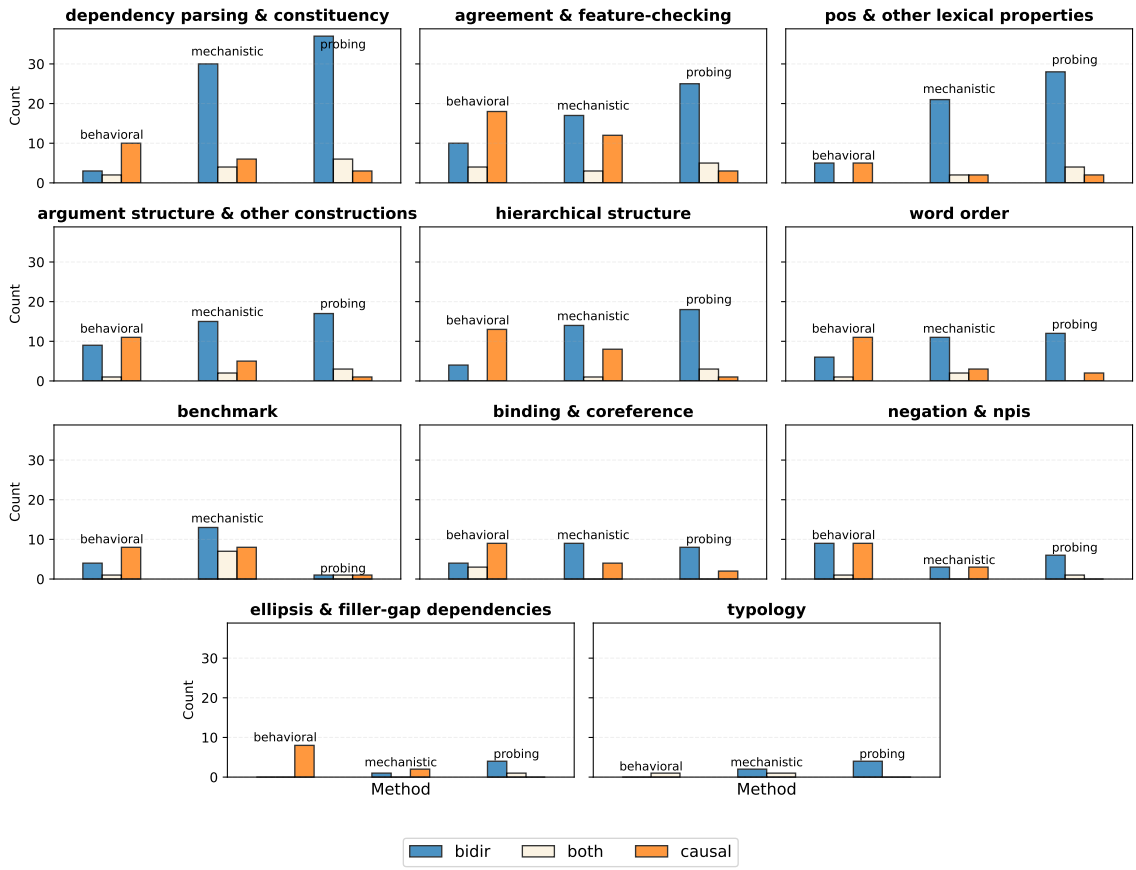


Figure 19: Distribution of studies in our database across syntactic phenomena, model type (bidirectional, causal, both TLMs types) and interpretability method, ordered by overall counts.

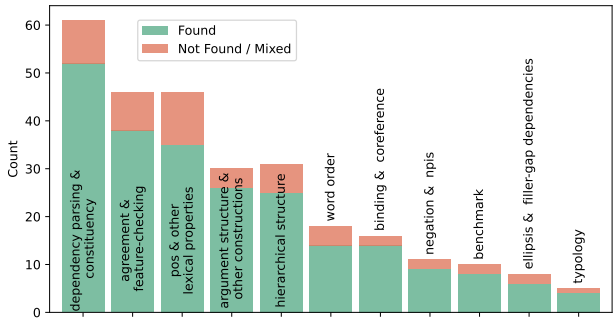


Figure 20: Successful recovery of syntactic information from TLMs' representations via probing across linguistic phenomena.

Overall few in counts, the mixed and critical findings suggest that models rely heavily on surface-level patterns rather than abstract syntactic rules, exhibiting limited and inconsistent sensitivity to structural changes. Also, TLMs' syntactic abilities vary across conditions, improving with more data and in high-resource languages but remaining weak in low-resource settings, and can even degrade with fine-tuning.

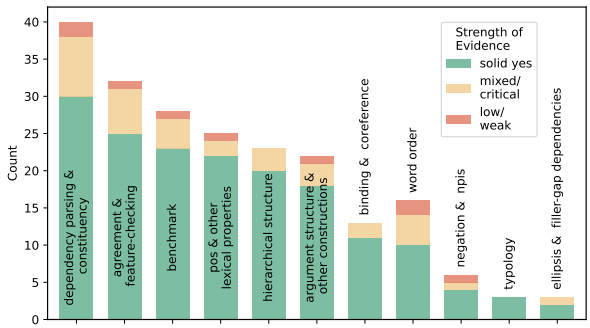
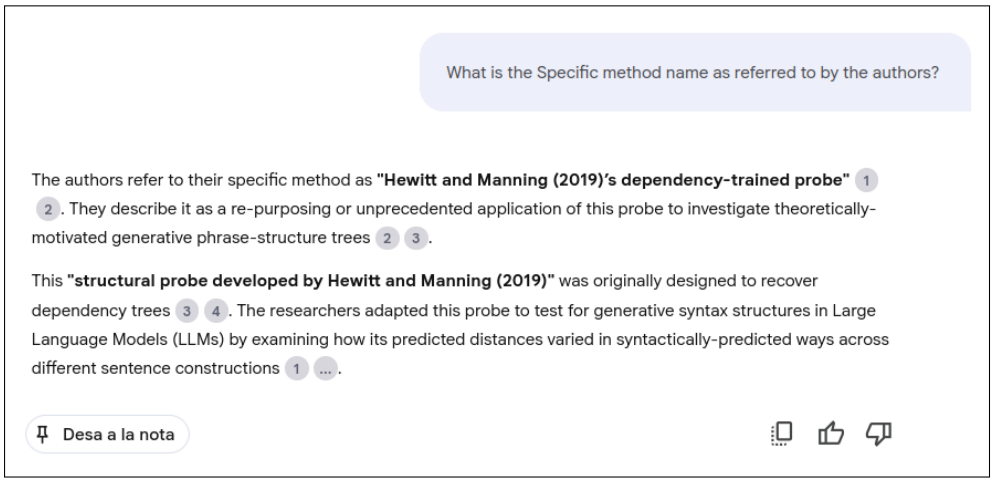


Figure 21: Evaluation of syntactic awareness in mechanistic interpretability studies by linguistic phenomena tested.



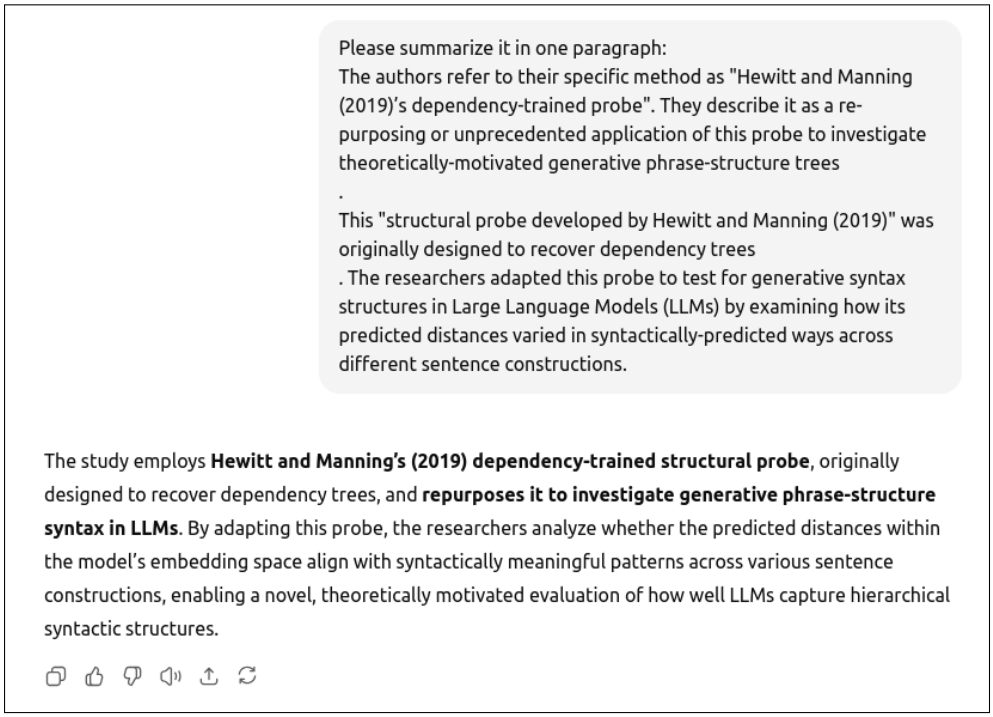


Figure 22: Illustration of the AI-based workflow. **Top:** NotebookLLM (Google Labs, 2023) interaction depicting how the model assists with information extraction; numbers refer to the original source in the paper. **Bottom:** Example of a ChatGPT (OpenAI, 2025) session showing a query and the generated response.

You are evaluating textual information. Given a paragraph and a note, which are based on the same source, rate how much the note captures the information of the paragraph on a scale from 0 to 5, where 0 = unrelated and 5 = fully equivalent.

1 majority of the information about the syntax tree of a sentence is in fact extractable by the model. This, however, is not true for randomly initialised trans- former models. results, thus, lead us to conclude that a transformer's training leads its attention heads to have the potential to decode syntax trees.

#2 demonstrates that transformer-based language models (LMs) like BERT, ALBERT, and RoBERTa have a high potential to extract syntactic information from sentences, as measured by the Architectural Bottleneck Principle and attentional probes. Using V-information, the study found that these models could access roughly 85% of syntactic information in English sentences, with similar trends across other languages, and that this information is most extractable in the middle layers. Importantly, this syntactic knowledge emerges from pretraining rather than being inherent to the architecture. However, while attention heads could use this information, the study shows they do not actually compute weights resembling syntax trees, leaving the question of actual usage open. Methodologically, the study also highlights that simpler structural probes underestimate LMs' potential, as the attentional probe recovered more syntactic information than previous baseline methods.

I would rate the note's coverage of the paragraph as **3 out of 5**.

Figure 23: Instance of a ChatGPT (OpenAI, 2025) prompt showing our evaluation query with an example.